Neurally-inspired robotic controllers implemented on neuromorphic hardware

Milde, Moritz B ; Sumislawska, Dora ; Sandamirskaya, Yulia ; Indiveri, Giaocomo

Neurally-inspired robotic controllers implemented on neuromorphic hardware

Authors: Moritz Milde, Yulia Sandamirskaya, Giacomo Indiveri

Affiliation: Institute of Neuroinformatics, University of Zurich and ETH Zurich

Summary
Neurorobotics aims to use models of biological neural systems to design efficient and adaptive robotic controllers. For complex, perception-driven behaviors, such neuronal controllers require substantial computational time and resources when simulated in software. However, these controllers can be implemented in an efficient way using neuromorphic hardware systems. Here, we present two neural-dynamic architectures, implemented with a neuromorphic VLSI device for controlling simple robot behaviors: a reactive collision avoidance strategy and a spatio-temporal feature extraction to estimate relative visual motion. We demonstrate how these architectures may be realized in neuromorphic robotic agents.

Zusammenfassung
Insekten vollbringen faszinierende Kollisionsvermeidungsmanöver und nutzen gleichzeitig sehr wenig Rechenresourcen. Neurorobotik nutzt ebendiese Vorbilder neuronaler Informationsverarbeitung um effiziente und adaptive Kontrollstrategien für Roboter zu implementieren. Simulationen von komplexen, Perzeption getriebenen Verhaltensstrategien sind sehr rechenintensiv, was eine lange Rechenzeit zur Folge hat. Diese Kontrollstrategien können jedoch Recheneffizient auf neuromorphen Systemen implementiert werden. Im Folgenden demonstrieren wir wie neuronale Architekturen zur einfachen Hindernisvermeidung und zur Extraktion von relativen Bewegungsinformationen, umgesetzt auf neuromorphen VLSI Systemen, erfolgreich genutzt werden können um das Verhalten von neuromorphen Robotern zu kontrollieren.

Introduction
Any mobile agent, whether robotic or biological, has to avoid collisions in order to navigate safely through the environment. Insects are particularly interesting as source of inspiration for collision avoidance, since their computational primitives have to be robust against noise and perturbations. The way sensory information is processed in these insect brains to execute a collision avoidance strategy is drastically different from what is typically done in conventional robotic controllers.

Neuromorphic processors are full-custom brain-inspired devices comprising arrays of silicon neurons and adaptive synaptic circuits. An example of such a device is the Reconfigurable On-Line Learning (ROLLS) device [5] shown in Fig. 1 (left box).

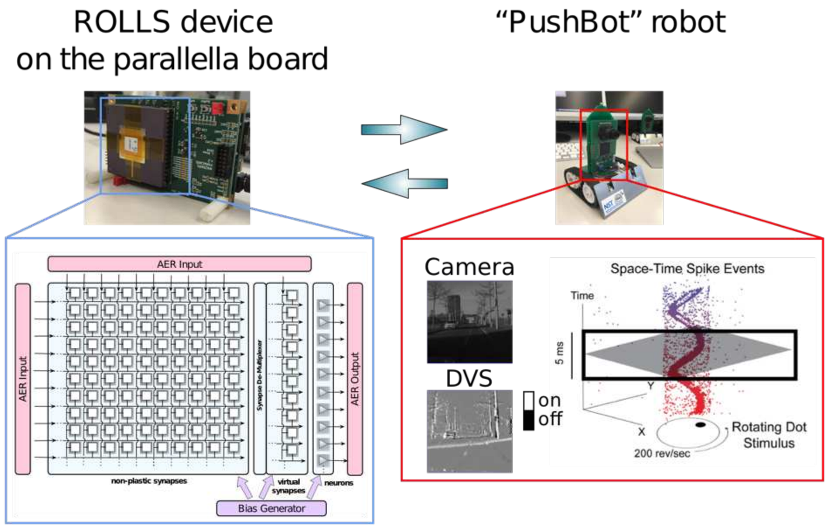

Fig.1. The experimental setup. ***Left:*** *The ROLLS neuromorphic processor, with an array of 512x256 dynamic synapses and 256 adaptive exponential Leaky Integrate and Fire (LIF) neurons. [5].* ***Right:*** *The robotic platform "PushBot" with a DVS sensor, and the working principle of the DVS. Each pixel responds asynchronously to a relative change in temporal contrast and emits either an "on" event (white), luminance increase or an an "off" event (black), luminance decrease.* ***Bottom right:*** *Spatio-temporal structure of the event stream when the DVS is stimulated with a rotating dot (adapted from [7]).*

This neuromorphic processor allows us to implement spiking neural networks that can process directly the information provided by event-based sensors, such as the Dynamic Vision Sensor (DVS) [2]. The DVS is inspired by the working principle of the mammalian retina. Each pixel of the DVS responds to relative changes in temporal contrast and elicits an event in real-time. Rather than producing sequences of frames like normal cameras, the DVS produces a continuous stream of spikes (see Fig. 1, right box).

Here we implement a spiking model of the insect vision system on the ROLLS chip to compute a steering control signal for the robotic agent.

Specifically, we show two instances of neurally-inspired robotic controllers: a reactive collision avoidance scheme inspired by the Braitenberg-vehicle principle, and an Elementary Motion Detector (EMD) inspired by the fly visual system.

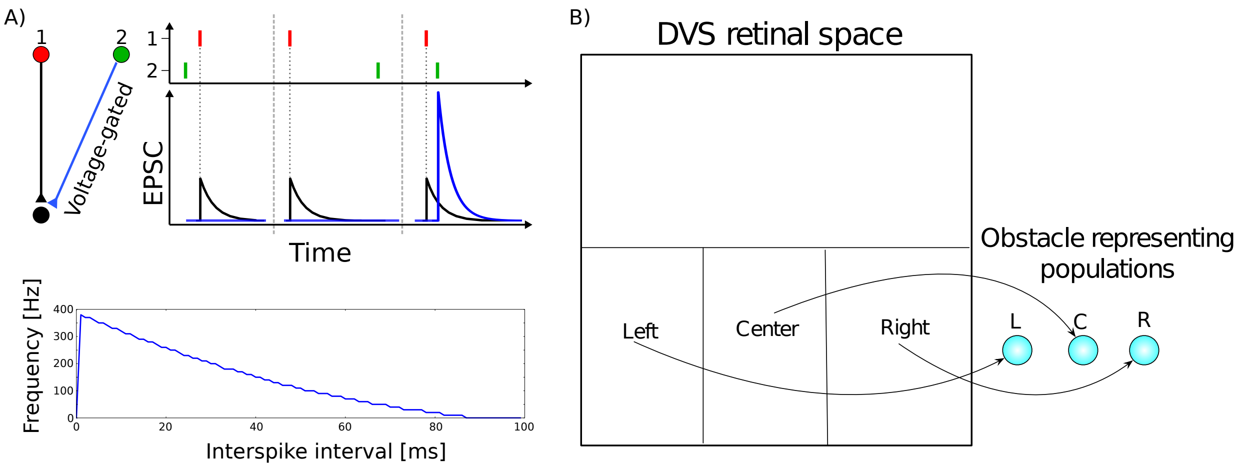

Fig.2: Neural architectures. A) Working principle of the spiking Elementary Motion Detector. B) Collision avoidance neuron population for the three possible steering direction of the autonomous driving agent.

The collision avoidance setup uses a Pushbot robot with the embedded DVS [6], while the spiking EMD uses the standard DVS mounted on top of the wheeled robotic platform Pioneer 2-DX.

Obstacle avoidance

The obstacle avoidance strategy used is the following: when the robot senses a large amount of events from one side of the camera image, it drives its motors on in the opposite side. We considered events from the lower half of the DVS for obstacle avoidance, since this region corresponds to close-by objects. This part was divided into three regions, representing obstacles on the left side, right side, and in the center.

On the ROLLS chip, we defined three populations of 20 neurons, each representing the respective position of the perceived obstacle ("left", "right", and "center"). Each neuron in these populations received an input spike for every event from the corresponding portion of the DVS sub-region (see Fig. 2, B). Both synaptic and neural dynamics of the ROLLS circuits stabilize the temporal dynamics of the system. The population response averages out the spatial effects of noise and circuit variability. We connected the three neuron populations on the ROLLS with mutually inhibitory connections.

In addition, we defined two pairs of neuronal populations that represent the velocity of the left and right wheels of the robot in the forward and backward direction, respectively. These populations were connected to the "left"-"center"-"right" neural populations in a way that realizes avoidance behavior: left/right obstacle populations excited the left/right wheel forward populations, while the center obstacle population excited both left and right wheel backward populations. This led to avoiding obstacles to the left and right from the robot and to a "retreat" maneuver for an obstacle or large clutter in front of the robot.

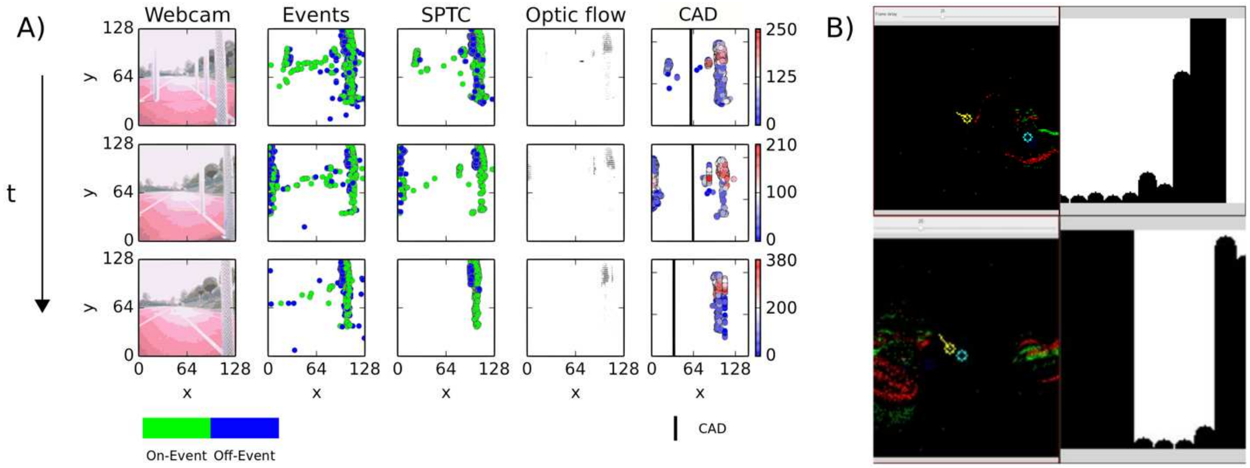

Fig. 3: Prediction of Collision Avoidance Direction (CAD). A) sEMD/Optic flow based estimate. B) Neural population activity use for the obstacle avoidance control strategy

Spiking Elementary Motion Detector

The spiking Elementary Motion Detector (sEMD) [4] we propose is adapted from the correlation-type EMD model [1].

To increase robustness to noise, a spatial neighborhood of 3 x 3 pixels of the DVS is projected to one so-called Spatio-Temporal Cuboid (SPTC) neuron. For the sake of simplicity let's consider two SPTC (1, 2) neurons and one sEMD neuron (Fig. 2, A), with one regular synapse connecting the left SPTC (1) neuron and one voltage gated synapse connecting the right SPTC (2) neuron with the sEMD neuron (Fig. 2 A, right synapse). The voltage gated synapse is only active if the post-synaptic membrane potential is above a certain threshold. Furthermore, the regular synapse is tuned so that if there is no spike provided by the right SPTC neuron, the sEMD neuron will not produce any output spikes. Hence, the sEMD neuron is only sensitive to one direction of motion:

If the left SPTC neuron spikes at t_0, then the membrane potential rises slightly. If then the right SPTC neuron emits a spike at 1 ms < t_1 < 80 ms, the post-synaptic membrane potential is driven above the threshold and the neuron spikes (Fig. 2 A, second and third column). The synaptic weight of the voltage gated synapse is multiplied by the synaptic current of the regular synapse and added to the synaptic current of the voltage gated synapse. In this way the inter-spike interval between two neighboring SPTC neurons is transformed into an instantaneous firing rate, which decreases with increasing inter-spike intervals (Fig. 2 A, lower plot). See [4] for a detailed description of this model.

If the robot moves on a purely translational trajectory, the firing frequency of the sEMD correlates with the amplitude of translational optic flow and thus, scales with distance to nearby objects.

Results

Obstacle avoidance

We tested the Pushbot in a real-world scenario and verified how the robot could robustly avoid obstacles in its way at a high speed (for a detailed analysis of results see [3]).

Optic flow based Collision avoidance

For testing the second avoidance strategy, the robot was manually steered with a constant velocity through a set of cylindrical obstacles (Fig. 3, A first column). The events elicited by the DVS are pre filtered by the SPTC neurons (Fig. 3, A second and third column) and their activity was used to drive the sEMD neurons (Fig. 3, A), fourth column). As expected, the firing rate of the sEMD neurons correlates with the object distance (see last column of Fig. Results, A). Note that the sEMD is very sensitive and can distinguish the relative distance along the object, i.e. the bottom part of the obstacle is farther away from the DVS than the top part.

Discussion

We presented two approaches to control a robotic platform using an event-based camera as only sensory information and LIF neurons to compute a collision avoidance direction.
Both approaches can be implemented on a neuromorphic processor. These two properties make them optimally suited for robotic applications, due to the low power consumption compared to conventional frame-based approaches.

Bibliography

[1] Hassenstein, B. and Reichardt W. "Systemtheoretische analyse der zeit-, reihenfolgen-und vorzeichenauswertung bei der bewegungsperzeption des rüsselkäfers chlorophanus." *Zeitschrift für Naturforschung B*, 1956: 513 - 524.
[2] Lichtsteiner, P., Posch, C., and Delbruck, T. "A 128 X 128 120db 30mw asynchronous vision sensor that responds to relative intensity change." *IEEE International Solid State Circuits Conference.* IEEE, 2006.
[3] Milde, M. B., Dietmüller, A., Blum, H., Conradt, J., Indiveri, G., Sandamirskaya, Y. "Simple robot navigation with a neuromorphic device [in prep]." *Frontiers*, 2016.
[4] Milde, M. B., H, Egelhaaf, M., Chicca, E. "Biomimetic asynchronous event-driven collision avoidance spiking neural network based on optic flow[in preperation]."
[5] Qiao, N., Mostafa, H., Corradi, F., Osswald, M., Sumislawska, D., Indiveri, G. "A Reconfigurable On-line Learning Spiking Neuromorphic Processor comprising 256 neurons and 128K synapses." *Frontiers in neuroscience*, 2015.
[6] Müller, G. R. and Conradt, J. "A miniature low-power sensor system for real time 2D visual tracking of LED markers." *IEEE International Conference on Robotics and Biomimetics, ROBIO 2011.* IEEE, 2011.
[7] Mueggler, E., Forster, C., Baumli, N., Gallego, G. and Scaramuzza, D. "Lifetime Estimation of Events from Dynamic Vision Sensors." *2015 IEEE International Conference on Robotics and Automation (ICRA).* IEEE, 2015. 4874 - 4881.